Tourism Management 106 (2025) 105022

Contents lists available at ScienceDirect

Tourism Management

journal homepage: www.elsevier.com/locate/tourman

Beyond static rankings: A tourist experience-driven approach to measure destination competitiveness

Jinyan Chen[a,*], Jie Wu[a], Dan Wang[a], Bela Stantic[b]

[a] School of Hotel and Tourism Management, The Hong Kong Polytechnic University, Hong Kong
[b] School of Information and Communication Technology, Griffith University, Australia

ARTICLE INFO

Keywords:
Destination competitiveness
Social media
Dynamic McKinsey matrix
Sentiment analysis
Destination management
Big data analytics

ABSTRACT

In the dynamic field of destination management, maintaining a destination's competitiveness requires understanding the evolving preferences of tourists. However, current research often adopts a static approach, failing to capture the dynamic nature of tourist needs and the evolving competitiveness of a destination. To address this, we introduce a novel approach using user-generated content from various social media platforms over a six-year period to assess key attributes that influence destination competitiveness. The results indicate that attributes in deciding destination competitiveness are not fixed, with some remaining stable factors in competitiveness, while others fluctuate over time. Attributes that even alter their competitive standing could significantly impact overall destination competitiveness. This research contributes a dynamic model that allows destination managers to adapt strategies in real time, aligning with current market conditions and enhancing competitiveness in the tourism industry.

1. Introduction

In the constantly evolving field of tourism management, destination competitiveness is crucial in attracting tourists and driving tourism expenditure. Destinations are required to continually adapt and innovate to maintain their appeal and stay ahead of competitors as market conditions evolve rapidly. Traditionally, the assessment of destination competitiveness has focused on economic stability, infrastructure, and policy environments. However, these factors alone do not fully address the changing preferences and behaviours of tourists, which are increasingly influenced by personal experiences and subjective perceptions. A deep understanding of destination competitiveness involves exploring tourist experiences and emerging trends. How tourists evaluate their experiences at the destination is important for the destination, as positive experiences can be leveraged for effective marketing and building customer loyalty.

Destination competitiveness is multifaceted and has been the subject of extensive scholarly discussion, underscoring its complexity and varied interpretations. Azzopardi (2011) emphasised the need for destinations to remain competitive, as tourists ultimately choose a destination based on its attractiveness. Thus, destinations need to strive to improve their attractiveness and cater to tourists' preferences to gain a competitive advantage over other destinations. With the increased attention to this field, various models have been proposed for assessing destination competitiveness. For instance, Ritchie and Crouch (2003) introduced a macro perspective, emphasizing the need for destinations to be environmentally, socially, and culturally sustainable. This model has been foundational due to its broad and integrative approach, which considers not only economic but also non-economic factors that contribute to the long-term viability of destinations. Crouch (2011) expanded on this by proposing a model comprising 36 features that assess destination competitiveness more granularly, reflecting the complexity and multifaceted nature of what makes a destination competitive. Further evolving the concept, Abreu Novais et al. (2018) recommended evaluating destinations across four dimensions: economics, attractiveness, satisfaction, and sustainability. This model highlights the necessity of a balanced approach that incorporates both quantitative economic metrics and qualitative assessments of tourist satisfaction and destination appeal.

However, destination competitiveness is an evolving construct, not a static model, responding dynamically to various factors over time. This necessitates a continuous re-evaluation of strategies and adaptability to

* Corresponding author.
E-mail addresses: Jinyan.chen@polyu.edu.hk (J. Chen), jie-shtm.wu@polyu.edu.hk (J. Wu), d.wang@polyu.edu.hk (D. Wang), b.stantic@griffith.edu.au (B. Stantic).

https://doi.org/10.1016/j.tourman.2024.105022
Received 15 December 2023; Received in revised form 25 July 2024; Accepted 30 July 2024
Available online 9 August 2024

new trends, such as shifts in tourist preferences or changes in global economic conditions. As destinations evolve, the approaches to maintaining competitiveness must revolute, including leveraging technology and data analytics to better understand and react to visitor behaviors and preferences in real time, as well as integrating sustainability into core development strategies to meet the increasing demand for responsible travel options. For example, traditional models, like those by Porter (1980) and further elaborated by Ritchie and Crouch (2003), underscored the importance of understanding long-term dynamics that influence how destinations develop and maintain competitive advantages, which are foundational in understanding how destinations develop and sustain competitive advantages. Despite these advancements, one area that destination competitiveness has not yet fully achieved is the capability to swiftly and accurately adapt to rapid changes in tourist experiences and perceptions in real time. A dynamic model from the customer's perspective is important because it allows for a more comprehensive and deep understanding of destination competitiveness. By redefining market attractiveness to reflect tourist sentiment and competitive strength to encompass destination attributes, we can better capture the evolving nature of tourist preferences and behaviours. This is crucial in today's rapidly changing global tourism market, where tourist expectations and needs are constantly shifting. A dynamic model also enables destinations to react more effectively to these changes, ensuring they remain competitive and appealing to tourists.

Given the complexities of destination competitiveness, there is a critical need for a robust framework that evaluates destination competitiveness through the lens of tourist experiences. This approach not only aligns with modern consumer behaviour trends, where experiential aspects significantly shape preferences and perceptions but also allows destinations to strategically position themselves by identifying strengths and areas for improvement. Nowadays, the introduction of the internet, social media, and big data analytics has significantly renewed interest in destination competitiveness. These technologies allow us to understand how the competitiveness of a destination can fluctuate based on the changing preferences and needs of tourists. The rising use of social media and online review platforms can alter the perception and attractiveness of destinations based on traveller reviews and shared experiences. By analysing such data, stakeholders can gauge the dynamic shifts in what tourists value most at any given time, allowing for more responsive and targeted management strategies. The integration of big data into tourism research has opened avenues for more nuanced and real time analyses, particularly in the context of smart destinations and sustainability issues (Cimbaljević et al., 2019; Fyall & Garrod, 2020; Soares et al., 2021).

To address the evolving nature of destination competitiveness, this study introduces a novel analytical framework that utilizes big data to capture real time changes in tourist experiences and preferences. Our methodology involves a dynamic strategic analysis tool that leverages data from multiple social media platforms, thus providing a comprehensive timeline of how destination competitiveness changes in response to significant events and trends. Specifically, the following research questions are answered:

1. How can destinations evaluate their competitiveness from the perspective of tourists' experiences?
2. How does the competitiveness of destinations change over time in relation to tourists' experiences?
3. How can these changes in destinations be assessed?

2. Literature review

2.1. Concept of destination competitiveness

The concept of destination competitiveness in tourism studies refers to the ability of a destination to attract and satisfy potential tourists effectively compared to other destinations, such as opening up opportunities for identifying product deficiencies, deriving effective strategies for strengthening business (Gao et al., 2018; Liu et al., 2021). However, attracting tourists to destinations is becoming more competitive because tourists are increasingly seeking unique experiences. In particular, their expectations and decision-making have been impacted by new trends and products that have emerged with the development of new media, such as online reviews and social media (Leung et al., 2013). Therefore, meeting tourists' needs is an effective way to enhance destination competitiveness (Kubickova & Martin, 2020; Lai et al., 2021; Lopes et al., 2018; Mior Shariffuddin et al., 2022).

Historically, the assessment of destination competitiveness has considered various factors including natural and cultural resources, infrastructure, accessibility, image, and price. Ritchie and Crouch (2003) laid down a foundational framework that emphasizes the importance of these elements, suggesting that destination competitiveness should be environmentally, socially, and culturally sustainable. Over time, this framework has evolved to incorporate additional dimensions such as economic factors, attractiveness, satisfaction, and sustainability, as suggested by recent studies (Abreu Novais et al., 2018; Chen et al., 2022; Dwyer & Kim, 2003; Lee & Park, 2023; Li, Li, et al., 2022). Table 1 presents a summary of the recent literature on destination competitiveness to facilitate a thorough understanding of the concepts. It can be seen that destination competitiveness has been increasingly examined from the tourist perspective.

However, traditional models of destination competitiveness often adopt a static view, failing to account for the changing dynamics of tourist preferences and behaviours. As tourism is an extremely dynamic industry, influenced by numerous external and internal factors ranging from global economic conditions to social trends, the static nature of traditional competitiveness models limits their utility in practical destination management (Shakibaei et al., 2021; Zheng et al., 2021). As Blazquez-Resino et al. (2022) remarked, the reshaping of behaviours might be a long-term trend that is unlikely to be reversed in the near future. The dynamic nature of destination competitiveness, as highlighted by Porter's Competitive Advantage of Nations Model, underscores the need for a sustained and adaptive approach to understanding how destinations can maintain their appeal and effectiveness in attracting tourists. While Ritchie and Crouch (2003) have extensively discussed the various factors contributing to destination competitiveness, including both endowed and created resources, there remains a gap in the literature regarding the rapid and real time monitoring of changes in tourist experiences and perceptions.

From a tourist experience perspective, the changing preferences or needs could be reflected in their choice of destination, even a very short-term and even immediate evolution of the image or attractiveness of the destination could impact the destination's competitiveness. Therefore, it is critical to consider that with the advent of the internet, social media, and big data, the capability to analyse the immediate and very short-term dynamics of destination competitiveness, particularly from the perspective of tourist perceptions, has significantly enhanced.

2.2. Modelling destination competitiveness

Given the importance of product/service competitiveness, various disciplines have proposed approaches to analyse competitiveness. Overall these data can be divided into two streams, namely traditional data-based (e.g., surveys, questionnaires and interviews) and User-Generated-Content based.

2.2.1. Traditional data-based studies

Traditional studies primarily involve surveys, questionnaires, interviews, and the utilisation of strategic analysis tools. For example, Dyson (2004) adopted a strength, weakness, opportunity, and threat (SWOT) analysis to understand the focal company's strengths, weaknesses, opportunities and threats. Pesce et al. (2018) used SWOT analysis to investigate the influence of environmental control policies on

Table 1
Summary of representative literature on destination competitiveness.

Perspective	Data	Research scope	Researcher	Dynamics
Socio-economic	Qualitative surveys	Investigated how cluster factors (e.g., government, DMOs, Universities, and companies) affect destination competitiveness	Chin et al. (2017)	No
Socio-economic	Structured interviews, questionnaires and secondary data sources	Used multi-source data to explore destination image	Tegegne et al. (2018)	No
Economics	Questionnaire	Utilised Rasch Measurement Theory (RMT) to measure the construct "competitiveness of tourism zones of Tenerife"	Parra-López and Oreja-Rodríguez (2014)	No
Economics	Surveys	Measured destination competitiveness at the regional level	Lopes et al. (2018)	No
Economics and resources	Travel & Tourism Competitiveness Report	Proposed a weighted composite indicator of destination competitiveness	Gómez-Vega and J Picazo-Tadeo (2019)	No
Resources	Based on literature	Defined key determinants of destination competitiveness, including endowed (inherited) resources and created resources	Dwyer and Kim (2003)	No
Tourism niche	Online survey	Investigated the competitiveness of diving destinations under different tourism niches (e.g., tourist groups with different levels of travel experience).	Neto et al. (2020)	No
Cross-cultural	User-generated content (UGC) and survey	Investigated a cross-cultural destination image based on mixed methods	Lee and Park (2023)	No
Tourists and travel agency	Survey	Adopted tourism destination competitiveness (TDC) to determine the strengths and weaknesses of the destination (Miyagi Zao region)	Murayama et al. (2022)	No

Note: 'Temporal dynamics' indicates whether the study considered the temporal dynamics of destination competitiveness from the tourist experience perspective.

companies and to clarify the competitive landscape of enterprises. Another notable qualitative approach is the five-force model proposed by Porter (1980), which analyses competitiveness in five dimensions: competition in the industry, the potential of new entrants into the market, the power of suppliers, the power of customers, and the threat of alternative products.

More recently, Importance–performance Competitor Analysis (IPCA) has been proposed to qualitatively divide product/service aspects into four categories (i.e., Quadrant I, II, III, IV) with different priorities (Albayrak, 2015; Albayrak & Caber, 2015). For instance, Albayrak (2015) first constructed the IPCA to reveal the competing positions of two hotels. Structural equation modelling is the tool most widely used (Liu et al., 2021) to analyse the relationship between product/service competitiveness and factors such as innovation strategies, customer satisfaction, and product pricing (Gupta et al., 2016; Yonezawa & Richards, 2016).

2.2.2. User-Generated-Content (UGC) based studies

With the rise of digital platforms, UGC has become a significant data source for analysing destination competitiveness. This method involves analysing content created by users on social media platforms, blogs, and review sites to gauge public sentiment and preferences. The use of UGC allows researchers to tap into real time data, reflecting contemporary tourist experiences and opinions. For instance, Cheng et al. (2021) developed a UGC-based SWOT analysis and conducted experiments to understand the competitive position of products in the market. Bi et al. (2019) clarified that they first utilised online reviews to develop an Importance-Performance Analysis and IPCA (Importance Performance Competitor Analysis) and further conducted a competitiveness analysis. Despite their popularity, these data typically divide product/service attributes into just four categories (i.e., strength/weakness/opportunity/threat for SWOT analysis and four quadrants for IPCA), which might be a rather coarse measure for understanding the subtleties of competitiveness.

Another popular competitiveness analysis approach relies on the use of sentiment embedded in UGC (Dickinger & Költringer, 2011; Gao et al., 2018; Yuan et al., 2022). The term 'sentiment' encompasses emotions, opinions, attitudes, and subjective expressions, indicating the underlying tone or subjective nature of the text, whether it is positive, negative, or neutral (Alaei et al., 2019; Chen et al., 2019). In sentiment analysis, 'sentiment' refers to individuals' expressed feelings, sentiments, or subjective judgments towards a particular subject, product, brand, or event (Serrano-Guerrero et al., 2015). As Wu et al. (2023) noted, customer sentiment can reflect competitiveness because it directly reflects customers' satisfaction, opinions, and preferences towards a product or brand. More specifically, positive customer sentiment indicates high levels of satisfaction with a product, and satisfied customers are more likely to become repeat customers, recommend the product to others, and contribute to positive word-of-mouth marketing. In contrast, negative sentiment suggests dissatisfaction, which can lead to customer churn and a decline in market share (Fernandes & Fernandes, 2018; Levy et al., 2013; Sparks & Browning, 2010).

2.2.3. Merits and limitations of different types of data

Both data types have their merits and limitations. Traditional data are structured and can provide in-depth insights but often do not capture the dynamic nature of market conditions and tourist preferences as effectively as UGC-based methods. On the other hand, while UGC is valuable for its immediacy and volume, it can suffer from issues of representativeness, the potential for misinformation, and privacy concerns, and also requires sophisticated analytical tools and skill to parse large datasets accurately. Despite these drawbacks, recent literature has effectively employed UGC data in destination competitiveness research. One of the studies tried not to solely rely on UGC but also integrate different data sources to create more robust models of destination competitiveness (Chen et al., 2022). Combining traditional survey data with insights gained from the sentiment analysis of UGC can offer a more nuanced understanding of competitive dynamics and allow for the monitoring of changes over time in tourist perceptions and experiences.

3. Methodology

3.1. Data collection

To evaluate changes in competitiveness over time, we analysed the social media posts of mainland Chinese tourists visiting Hong Kong, an important market segment for the city. To ensure comprehensive and unbiased results, data from two popular Chinese online platforms, Xiaohongshu and Dianping, were selected as data sources. Specifically, Xiaohongshu is one of China's largest social media platforms where tourists share their travel experiences, which is particularly valuable due to its large user base and the authentic, user-generated content that reflects genuine tourist sentiments and preferences (Huang et al., 2021). The authenticity and popularity of Xiaohongshu make it a rich resource for academic studies, as increasing numbers of researchers are turning to this platform to gather data on tourist behaviour and preferences (Cao, 2024; Li et al., 2023; Shan et al., 2024). Similarly, Dianping is a popular online platform in China, known primarily for its user reviews on destinations, restaurants, and hotels (Liu, Yu, et al., 2022). The platform's commitment to maintaining the authenticity of these reviews, such as implementing anti-cheat algorithms to prevent manipulated reviews and ensuring that the data gathered from Dianping are reliable and reflect true consumer opinions. Data collection was facilitated by Python language-based coding and the Octopus Collector, a widely used data collection tool. Relevant user posts were identified by manually searching for travel-related hashtags such as #HongKongTourism (香港旅游), #HongKongTravel (香港旅行), #HongKongTour (香港游), #HongKongTravelTips (香港游攻略), and #HongKongTravelPunchList (香港旅游打卡), resulting in 10,261 posts from February 28, 2018 to October 18, 2023. The URLs of these hashtags were then input into Octopus to automatically crawl the user posts. The details of the data are shown in Table 2.

To thoroughly assess destination competitiveness and understand the dynamic changes in tourists' experiences, the study framework divides the timeline into four distinct periods, each reflecting different phases of tourism activity in Hong Kong:

T1 **Pre-Pandemic Period (2018 to the start of the COVID-19 pandemic)** - This initial period serves as a baseline for understanding the state of tourism before any disruptions caused by the pandemic. It encapsulates typical tourist behaviours and destination dynamics prior to the pandemic;

T2 **Pandemic Impact Period (2020 to 2022)** - T2 is critical as it marks the period when the tourism industry was most directly impacted by the COVID-19 pandemic. This designation is based on the global timeline of the pandemic, where most severe disruptions to travel and tourism occurred, including travel bans, lockdowns, and significant reductions in tourist arrivals. This period is crucial for analysing the immediate impacts of the pandemic on tourist experiences and destination competitiveness;

T3 **Early Post-Pandemic Period (January 8, 2023 to May 22, 2023)** - This phase follows the reopening of borders and captures a specific type of tourism behaviour characterised by a surge in visits by mainland visitors to Hong Kong, primarily to reconnect with family and friends. This represents a shift from typical tourism patterns to more personal and relational travel, influenced by the easing of pandemic-related restrictions (Tsang et al., 2023);

T4 **Return to "new normal" (May 22, 2023 to October 20, 2023)** - The last period analysed is when the number of mainland visitors began to stabilise and gradually return to pre-pandemic levels. This phase is indicative of the recovery process and is essential for assessing how quickly and effectively the destination rebounded from the pandemic's impacts and what new or returning trends may define the future of tourism in Hong Kong.

3.2. Research design

Literature has shown that previous studies failed to capture the dynamic changes in destination competitiveness, particularly from a tourist perspective, addressing how different destination attributes are valued by tourists. The necessity to identify a destination's core strengths while monitoring changes in tourist interests is important for maintaining destination competitiveness. Traditional studies have struggled with these aspects due to a lack of valid data and the lack of direct modelling of the dynamics of this concept. This work shifts in focus from external to tourist experience-based factors in assessing destination competitiveness as it centres on the subjective experiences and perceptions of tourists, which are crucial drivers of a destination's appeal and success.

Table 2
Descriptive statistics of the data.

Topic	Number of posts	Number of users
#HongKongTourism (香港旅游)	5521	3697
#HongKongTravelPunchList (香港旅游打卡)	1678	980
#HongKongTravelTips (香港旅游攻略)	657	482
#HongKongTravel (香港旅行)	1702	1275
#HongKongTourTips (香港游攻略)	37	21

Note: 'Number of users' indicates the number of users identified by their unique user ID.

The McKinsey Matrix is generally used to evaluate two aspects of the performance of a company (or region) when competing with others, namely market attractiveness and competitive strength, as shown in Fig. 1. Based on these two indicators, the McKinsey Matrix is divided into nine quadrants, where numbers indicate quadrants and colours indicate competing positions. In this study, market attractiveness is reinterpreted to reflect tourist sentiment, which serves as a direct indicator of a destination's appeal based on the experiences and perceptions of tourists (Chen et al., 2022). Furthermore, competitive strength is measured by the importance of various destination attributes as perceived by tourists, which focus on tourist priorities as a critical enhancement over traditional models.

The use of the McKinsey Matrix in analysing destination competitiveness significantly enhances the understanding of destination competitiveness with a focus on tourist sentiment and the importance of destination attributes. This innovative approach addresses critical gaps in traditional destination competitiveness research by prioritising the direct perspectives of tourists, which are often marginalised in conventional models. By redefining market attractiveness to reflect tourist sentiment and competitive strength to encompass destination attributes, this study not only aligns more closely with contemporary tourist behaviours but also provides a more dynamic and responsive framework for assessing destination appeal.

The methodological framework developed in this study, as depicted in Fig. 2, is developed to ensure a comprehensive evaluation of destination competitiveness. The three key steps involved mining destination attributes, measuring these attributes, and modelling destination competitiveness, forming a cohesive process that transforms raw tourist data into strategic insights. This framework allows for a granular analysis of how destination attributes are perceived by tourists, thereby facilitating a more nuanced understanding of what drives destination competitiveness from a tourist perspective.

Step 1. Mining destination attributes

After performing part-of-speech tagging using *jieba*, a well-established Chinese word processing tool (Sun, 2012), we extracted nouns as the basis for discovering potential destination attributes, as

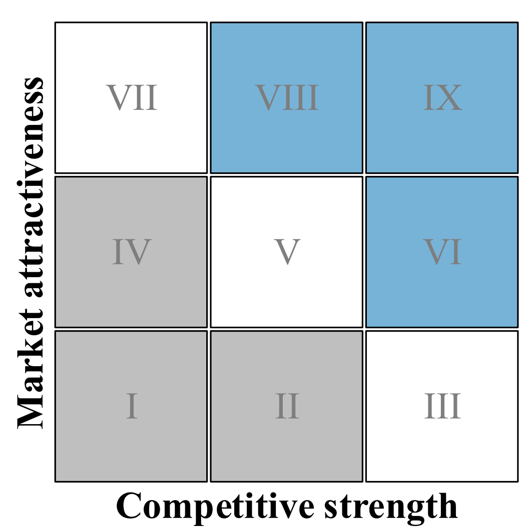

Fig. 1. Example of a McKinsey matrix.

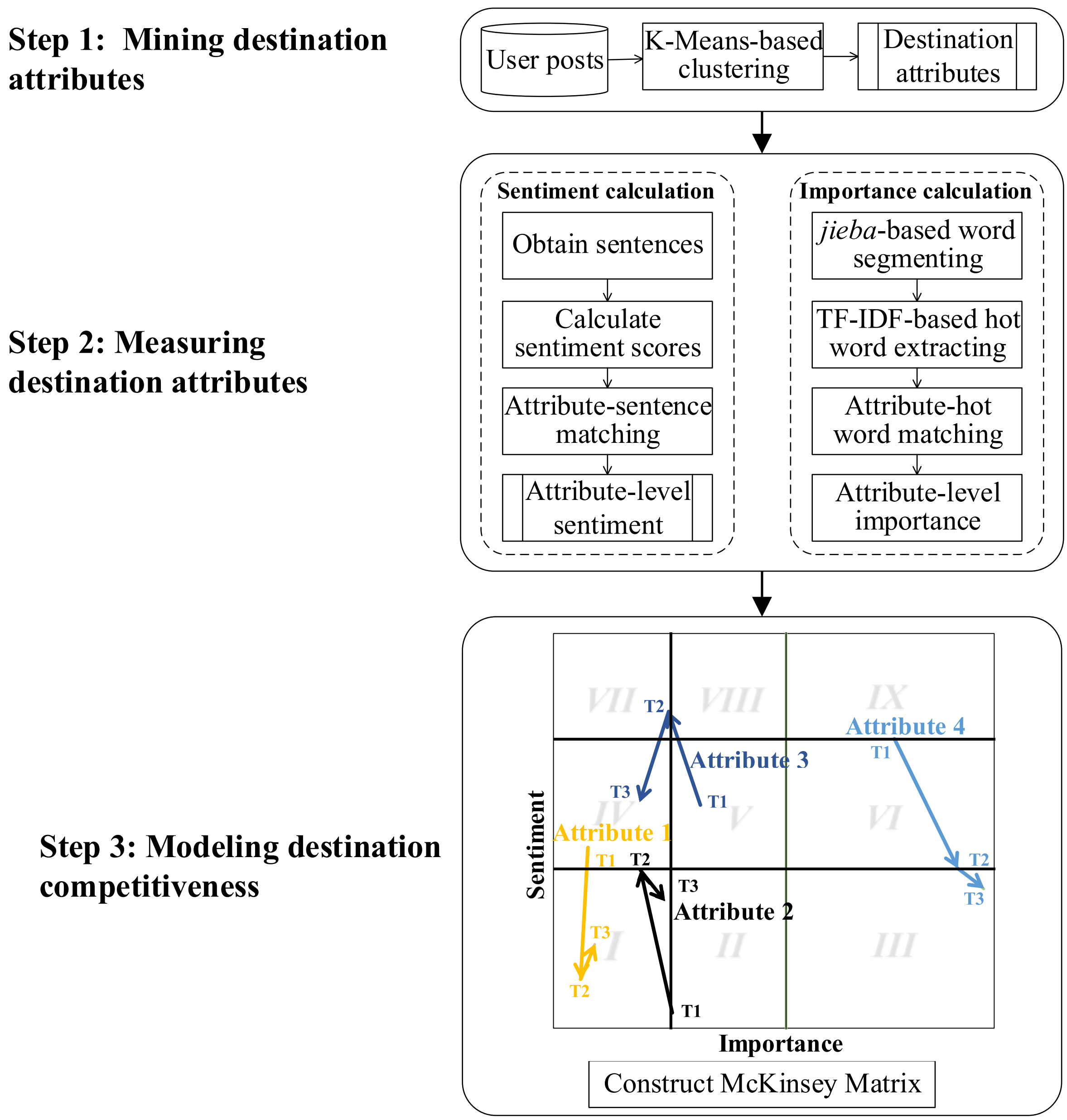

Fig. 2. The methodological framework developed for assessing destination competitiveness.

nouns are used to refer to specific objects. To automatically identify destination attributes, these nouns needed to be converted into word vector embeddings that could be processed and computed by computer programs. Research has found Bidirectional Encoder Representations from Transformers (BERT) to be an effective word embedding tool (Devlin et al., 2018) as it was trained on a huge text corpus. Therefore, we selected BERT to convert nouns into word embeddings. We adopted the K-Means algorithm, a well-developed and widely used method for discovering similar patterns in vector embeddings (Hall et al., 2017), to cluster the word embeddings of nouns to obtain various clusters. Similar clusters were then merged and labelled as destination attributes.

Step 2. Measuring destination attributes

Two indicators, the sentiment and importance of destination attributes, were calculated to construct the McKinsey Matrix.

(1) Sentiment calculation

Typically, sentiment calculation can be conducted using either the sentiment lexicon-based method or the deep learning-based method. Despite the simplicity of the former method, it is frequently criticised for its low accuracy because it ignores the semantic information in sentences (Ghiassi & Lee, 2018). To improve the method, researchers and practitioners have recently developed various calculation methods and tools based on deep learning techniques (Li, Ji, et al., 2022; Yang et al., 2024), with encouraging results. Among the deep learning-based methods, *paddlepaddle* (Baidu, 2018) is an open-source natural language processing kit developed by Baidu Corporation. It provides several advanced text mining algorithms, such as sentiment analysis and opinion extraction. *Paddlepaddle* (Baidu, 2018) offers a robust and efficient sentiment calculation model that can extract sentiment from text. Its sentiment analysis algorithm leverages the strength of deep learning techniques such as recurrent neural networks, long short-term memory networks, and convolutional neural networks to capture the contextual information and dependencies within the text. By training it on large datasets, the model learns to recognise and interpret sentiment patterns so that it can make accurate predictions on unseen text. A key advantage of *paddlepaddle*'s sentiment analysis algorithm is its flexibility and ease of use. It provides developers and researchers with an intuitive interface to deploy sentiment analysis models on their own datasets. Given these merits, *paddlepaddle* is widely adopted in industry and academia (Li et al., 2021; Zhang et al., 2021). Hence, we selected this advanced tool to analyse the sentiment in tourists' social media posts. Fig. 3 presents an overview of the process of calculating destination attribute-level sentiment using *paddlepaddle*.

Specifically, the process of sentiment calculation followed the work of Hu et al. (2019). First, online reviews were segmented into sentences; next, by calling the sentiment calculation model based on a convolutional neural network, the sentiment of each sentence and the corresponding sentiment score were calculated. To link the sentences to relevant attributes, an attribute lexicon based on the clustering results was constructed, which included both the attributes and the corresponding words describing them. Subsequently, sentences were matched to different attributes using the attribute lexicon. Finally, the attribute-level sentiment was calculated based on Equation (1), where i denotes the i-th attribute, n_i indicates the number of posts mentioning attribute i, and $sentiment_i^m$ represents the m-th post mentioning attribute i.

$$destination\_performance_i = \frac{\sum_{m=1}^{n_i} sentiment_i^m}{n_i} \tag{1}$$

(2) Importance calculation

Previous studies have demonstrated that tourists place varying degrees of importance on different destination attributes (Chen et al., 2022; Deng & Li, 2019; Rašovská et al., 2021). For instance, Rašovská et al. (2021) found that visitors to mountainous regions valued cleanliness, safety, and security the most, but were least concerned about transportation. By recognizing the importance of various attributes, organisations can tailor their efforts to meet their customers' needs and expectations and ensure their efforts are aligned with their target audience's priorities. Considering attribute importance can also help organisations to differentiate themselves from their competitors (Wu et al., 2023). By identifying attributes that are highly important to customers but are not well-executed by competitors, a destination can focus on improving those areas to gain a competitive advantage. Therefore, in this section, we propose a method for measuring the importance of destination attributes to illustrate the destination's competitive position.

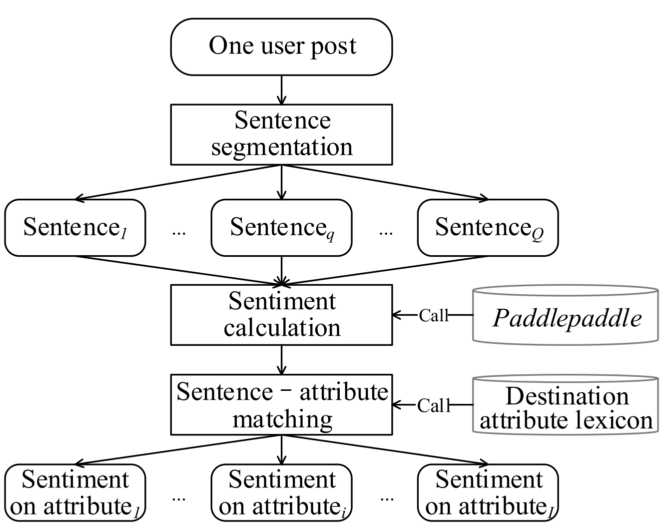

Fig. 3. Process of sentiment calculation.

Previous studies (e.g., Chen et al. (2022)) have calculated the importance of destination attributes based on how often tourists mention specific words (i.e., term frequency analysis). To improve this method and to avoid the bias arising from long documents, we propose the term frequency-inverse document frequency (TF-IDF) method. This method takes into account the importance of a term not only within a specific document but also within the entire corpus. It assigns weights to terms based on their frequency in a document (term frequency) and across all documents (inverse document frequency). TF-IDF makes it possible to identify important terms that occur frequently in a specific document but are relatively rare in the entire corpus, thus providing a better indication of their importance. Furthermore, the simple term frequency method assigns a high level of importance to common terms such as 'the' or 'and' that appear frequently in all documents. The TF-IDF method addresses this issue by assigning low inverse document frequency weights to such words to reduce their impact on term importance, thereby ensuring that less informative terms do not overshadow more meaningful terms. TF-IDF also takes into consideration the context in which a term appears within a document, including its position and neighbouring words. This captures important contextual information that can influence the meaning and significance of the term within the document, resulting in a more comprehensive assessment of the term's importance. In addition, term frequency alone can be biased towards terms that appear in longer documents, as they tend to have higher term frequencies due to the high word count. TF-IDF mitigates this bias by considering the inverse document frequency, which reduces the impact of document length on term importance and allows a fairer comparison of document importance regardless of length.

Given the significant advantages of the TF-IDF algorithm, in this study attribute importance was calculated based on this algorithm. The theoretical underpinning of this approach is salience theory (Guido, 1998), which posits that individuals allocate their attention to salient areas. Important attributes, therefore, are those that are frequently mentioned and discussed. In terms of the calculation process, *Jieba* (Sun, 2012) was adopted to segment sentences into words. We then applied the TF-IDF algorithm to extract salient words and their corresponding *tf-idf* values. Subsequently, the attribute lexicon constructed above was used to map these salient words onto different attributes. Finally, attribute-level importance was calculated based on the *tfidf* value using Equation (2), where i denotes the i-th attribute, k_i represents the total number of salient words under attribute i, and j indicates the j-th salient word.

$$destination\_importance_i = \sum_{j=1}^{k_i} tfidf_i^j \tag{2}$$

Step 3. Modelling destination competitiveness based on the McKinsey Matrix

We developed the dynamic McKinsey Matrix to model the dynamic changes in destination competitiveness. The matrix divides the horizontal and vertical axes into three parts, resulting in nine box grids that reflect different competitive positions. Specifically, these nine grids can be divided into three categories, represented by a grey area (i.e., Quadrants I, II, IV), a white area (i.e., Quadrants III, V, VII), and a blue area (i.e., VI, VIII, IX). Attributes that fall into different areas have different competitive positions. For instance, the blue area has higher sentiment performance and importance, and thus, attributes in this area are in a favourable competitive position.

Traditionally, the horizontal and vertical axes are divided equally into three parts; however, this can result in an uneven distribution of attributes within the matrix and low differentiation, wherein the majority of attributes fall into the same quadrant. Recent studies have adopted a non-uniform partitioning approach in which the axes are defined according to the research problem. For example, Shen et al. (2017) split the axes based on the level of sustainable urban development, which was more effective in overcoming the issue of uneven distribution. Therefore, in this work, we also partitioned the quadrants by calculating the upper and lower three quantiles of the horizontal and vertical axes to achieve an even distribution of attributes.

Fig. 4 shows an example of how attributes can be plotted in the dynamic McKinsey Matrix. First, the data are segmented into different periods: T1, T2, T3, and T4. Next, the matrix can be mapped by calculating the attribute-level sentiment and importance for different periods. The trajectories of the competitive positions of various destination attributes can then be captured.

4. Results

4.1. Identification of destination attributes

To categorise destination attributes effectively, section 3.2 showed a comprehensive methodology employing natural language processing and clustering techniques to do so. Initially, part-of-speech tagging was performed using the *Jieba* tool to extract nouns from the text, as these typically refer to specific objects relevant to destination attributes. These nouns were then transformed into word vector embeddings using the Bidirectional Encoder Representations from Transformers (BERT), known for its robust performance on large text corpora. Subsequently, the K-Means algorithm was applied to these embeddings to form clusters, leveraging its capability to identify similar patterns within the data. Similar clusters were merged and carefully labelled to represent distinct destination attributes, ensuring that the categorisation accurately reflected the characteristics of the nouns contained within each group.

We manually named the categories according to the keywords. More importantly, those attributes were cross-checked with Hong Kong destination attributes from current studies (Jiang et al., 2021; Lee & Park, 2023; Zhou & Chen, 2023). For example, Zhou and Chen (2023) identified nature (related to *Attraction*) and Culture (related to *Culture & Art*) as pivot aspects valued by tourists visiting Hong Kong. Similarly, Lee and Park (2023) found that seven factors constitute the destination image of Hong Kong such as general infrastructure (related to *Transportation*), tourist infrastructure (related to *Food* and *Shopping*) and culture (related to *Culture & Art*). In the end, seven attributes were identified: *Food*, *Shopping, Attraction, Accommodation, Transportation, Culture & Art*, and *Cross-border issues*. A detailed explanation for each attribute is shown in Table 3.

4.2. Destination attribute importance

The above results identified the attributes that matter to the destination, but we were also interested in whether tourists consider these attributes to be of equal importance. Table 4 presents the attribute importance results based on the TF-IDF algorithm's extraction of the salient words and their corresponding TF-IDF values.

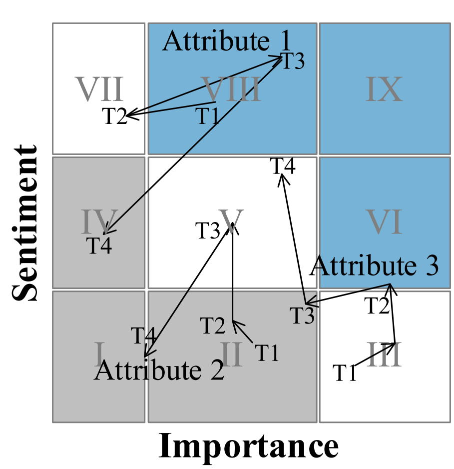

Fig. 4. Illustration of the dynamic McKinsey Matrix.

4.3. Destination attribute performance

The performance of the destination attributes was calculated using the sentiment analysis method outlined in Section 3.2. To facilitate a deeper understanding of destination performance in different periods, Fig. 5 illustrates the results in a box-whisker plot with the median, mean, upper quartile line (Q3), lower quartile line (Q1), maximum and minimum values, and outliers. An example of a Box-whisker plot is shown in Fig. 5a. The interquartile range, the difference between Q3 and Q1, reflects the degree of volatility of the data. The plots in Fig. 5b–h shows the changes in performance over the four periods. The X-axis represents the four time periods and the Y-axis presents the sentiment scores, which range from -1 to 1, where -1 indicates extremely negative performance and 1 denotes extremely positive performance.

The above figures show that most attributes were associated with positive sentiment, as the boxes are generally placed between 0.2 and 1. However, extremely negative comments increased over time. For example, Food followed a stable trend, but with an increase in extremely negative sentiment ($-0.069 \rightarrow -0.214 \rightarrow -0.367$). Attraction also showed a gradually decreasing trend ($0.761 \rightarrow 0.774 \rightarrow 0.781 \rightarrow 0.719$). Attribute such as Accommodation remained stable and became more positive over time. Shopping changed the most over the four periods, with a decrease in both the median performance ($0.771 \rightarrow 0.695 \rightarrow 0.836 \rightarrow 0.686$) and the mean performance ($0.723 \rightarrow 0.569 \rightarrow 0.651 \rightarrow 0.596$). There were also some positive trends; for example, Culture & Art showed an upward trend ($0.631 \rightarrow 0.701 \rightarrow 0.696 \rightarrow 0.736$) during and after the COVID-19 period. Tourists' destination experiences clearly changed over the period of the study. Understanding how to capture these changes and utilise them to assess destination development is important for various stakeholders. The following section explains how the dynamic McKinsey Matrix can be used to analyse destination competitiveness based on sentiment and importance.

4.4. Dynamic McKinsey matrix

Although previous studies have developed indicators to understand destination competitiveness, there is no direct model to measure the changes in destination competitiveness. Thus, we propose the improved McKinsey Matrix to capture the dynamics of destination competitiveness. Fig. 5 illustrates the resulting matrix, showing the evolving trajectories of the attributes. Different areas of the matrix represent different competitive positions: Quadrants I, II, and IV represent an uncompetitive position, Quadrants III, V, and VII represent a moderately competitive position, and Quadrants VI, VIII, and IX represent a highly competitive position.

Fig. 6 shows that the performance of all of the attributes constantly changed, with some attributes transitioning into different competition positions. This illustrates why it is critical to capture and understand the dynamics of destination competitiveness at the attribute level. In general, the attributes can be categorised into three groups based on their competitive position: *core*, *edge*, and *fluctuating* competitive attributes. Attraction and Culture & Art are categorised as core competitive attributes because of their advantageous positions. For example, Culture & Art transitioned into a highly competitive position (Quadrant VI → IX → VIII), while Attraction remained in a highly competitive position (Quadrant IX). Similarly, Richards et al. (2020) and Liu, Wang, et al. (2022) also stressed the critical roles of the culture and art of Hong Kong in contributing to its tourism market. Accommodation and Cross-border issues are classified as edge competitive attributes because they consistently occupied uncompetitive positions (Quadrants I, II, and IV). This suggests that the authorities should implement timely initiatives to improve the situation. Shopping and Food are classified as fluctuating competitive attributes due to their significant variations; in particular,

Table 3
Results of attribute clustering.

Food	Shopping	Attraction	Accommodation	Transportation	Culture & Art	Cross-border issues
Taste	Shopping	Marina	Room type	Metro	Culture	Hong Kong Dollars
Flavor	Visiting a store	Attractions	Hotel	Transportation	Museums	Pass
Ice cream	Shop	Night view	Accommodation	Cable car	Art	Cash
Milk tea	Convenience Store	Tickets	Rooms	Subway stations	The Forbidden City	Flow
Coffee	Bazaar	Excursions	Lobby	High-speed rail	Exhibition Center	Immigration
Dessert	Duty-free shop	Ocean Park	Boss	Passenger	Cultural Area	Exchange rates
Curry	Shop assistant	Hong Kong Island	Name of the store	MTR	Exhibition Halls	Documents
Cake	Markets	Seascape	Front desk	Airport	Residence	Gate
Bread	Inside store	Itinerary	Luggage	By Car	Works	RMB
Milk	Branch store	World	Apartment	Minibus	Art Museums	Nucleic acid testing

Table 4
Attribute-level importance.

Attribute/Period	T1	T2	T3	T4
Food	0.250	0.294	0.313	0.302
Shopping	0.134	0.134	0.122	0.122
Attraction	0.204	0.200	0.184	0.230
Accommodation	0.034	0.029	0.039	0.030
Transportation	0.113	0.091	0.091	0.089
Culture & Art	0.171	0.181	0.162	0.148
Cross-border issue	0.094	0.071	0.088	0.079

Note: 1. Importance values are normalised to (0,1) in each period. 2. T1 – before 2020, T2 –pandemic period 2020 to 2022, T3 – an early period after the opening of the border, and T4 – the late period after the opening of the border.

they both transitioned into disadvantageous positions (e.g., Shopping: Quadrant VIII→II→V). In comparison, previous studies (Lee & Park, 2023; Manosuthi et al., 2020) have usually highlighted that shopping is one of the most attractive activities for tourists in Hong Kong, but our findings reveal that shopping as a destination attribute of Hong Kong is losing its attractiveness.

4.5. *Factors influencing destination competitiveness*

In analysing factors that negatively impact a destination's competitiveness, it's evident that addressing tourists' negative experiences is crucial. Tourists' dissatisfaction with food and dining options due to restrictive policies, lack of amenities like hot water, and outdated decor significantly detract from the dining experience. Similarly, in the realm of shopping, a 'cash only' policy is increasingly becoming a point of contention, as tourists expect modern payment facilities such as mobile payments (Qu et al., 2018). Additionally, the poor attitude of shop staff further dampens the overall shopping experience. These factors, among others, highlight the importance of aligning destination attributes with evolving tourist expectations and preferences to maintain and enhance competitiveness in the global tourism market. The more detailed results are shown in Table 5.

Managing negative experiences in the tourism industry is pivotal for maintaining and enhancing competitiveness in the global market due to the direct impact on customer satisfaction, fostering loyalty and encouraging repeat visits, which are essential for maintaining a steady flow of tourism revenue (Chen et al., 2022). Additionally, negative feedback, when used constructively, serves as a powerful tool for continuous improvement, allowing destinations to adapt to evolving tourist expectations and technological advancements, thereby staying relevant and competitive in the market.

5. Conclusion and discussions

The literature review highlights a significant research gap in understanding the dynamic nature of destination competitiveness from a tourist experience perspective. Traditional models of destination competitiveness often focus on external factors and fail to adequately incorporate the subjective elements that significantly influence a tourist's experiences. To address this, we proposed a novel approach using user-generated content from various social media platforms over a six-year period to assess key attributes that influence destination competitiveness. By understanding the evolving nature of tourist preferences and needs, destinations can better evaluate their competitiveness and prioritise efforts to enhance their competitive edge in the rapidly changing global tourism market. This method can be applied to other destinations to capture changes in tourist experiences in relation to significant events and trends affecting travel behaviors.

In particular, following the original concept of destination competitiveness, which emphasizes the ability of destinations to attract tourists and generate tourism expenditure (Lee & Park, 2023; Ritchie & Crouch, 2003), we focused on the destination itself and examined its performance over time to understand the concept of destination competitiveness, without taking other competitors into account. Specifically, we first identified the destination attributes that were valued by visitors using the K-Means clustering algorithm. Sentiment analysis was then conducted to measure how the destination attributes performed over time. We developed a McKinsey Matrix-based dynamic model to capture the evolving trajectories of destination competitiveness. To further explore the factors leading to tourists' negative attitudes, we also applied an advanced natural language processing technique (i.e., opinion extraction based on *paddlepaddle;* Baidu, 2018) to investigate visitors' opinions.

We found that the attributes that were important to mainland Chinese tourists were Food, Shopping, Attraction, Accommodation, Transportation, Culture & Art, and Cross-border issues. Among these attributes, Food mattered the most across all periods, followed by Attraction, Culture & Art, and Shopping. In terms of destination competitiveness, all of the destination attributes exhibited varying performance, with some, such as Shopping and Food, even transitioning into different competitive positions. These findings strongly support our argument that understanding destination competitiveness from a dynamic perspective is of great importance for destinations to adapt to changing circumstances.

5.1. *Theoretical contributions*

This study introduces several theoretical contributions to the destination competitiveness literature, particularly by highlighting the dynamic nature of destination competitiveness and incorporating tourists' experiences as a central measure.

This study shifts the traditional focus of destination competitiveness from predominantly external competitive factors, such as economic and political conditions (Albayrak et al., 2021; Cracolici & Nijkamp, 2009), to the internal attributes of the destination, such as visitor experiences, which allows for a more detailed understanding of how destinations can leverage their inherent strengths and areas for improvement as seen through the eyes of tourists, thereby providing a more direct assessment of a destination's competitive ability.

Secondly, the study introduces a dynamic perspective to destination

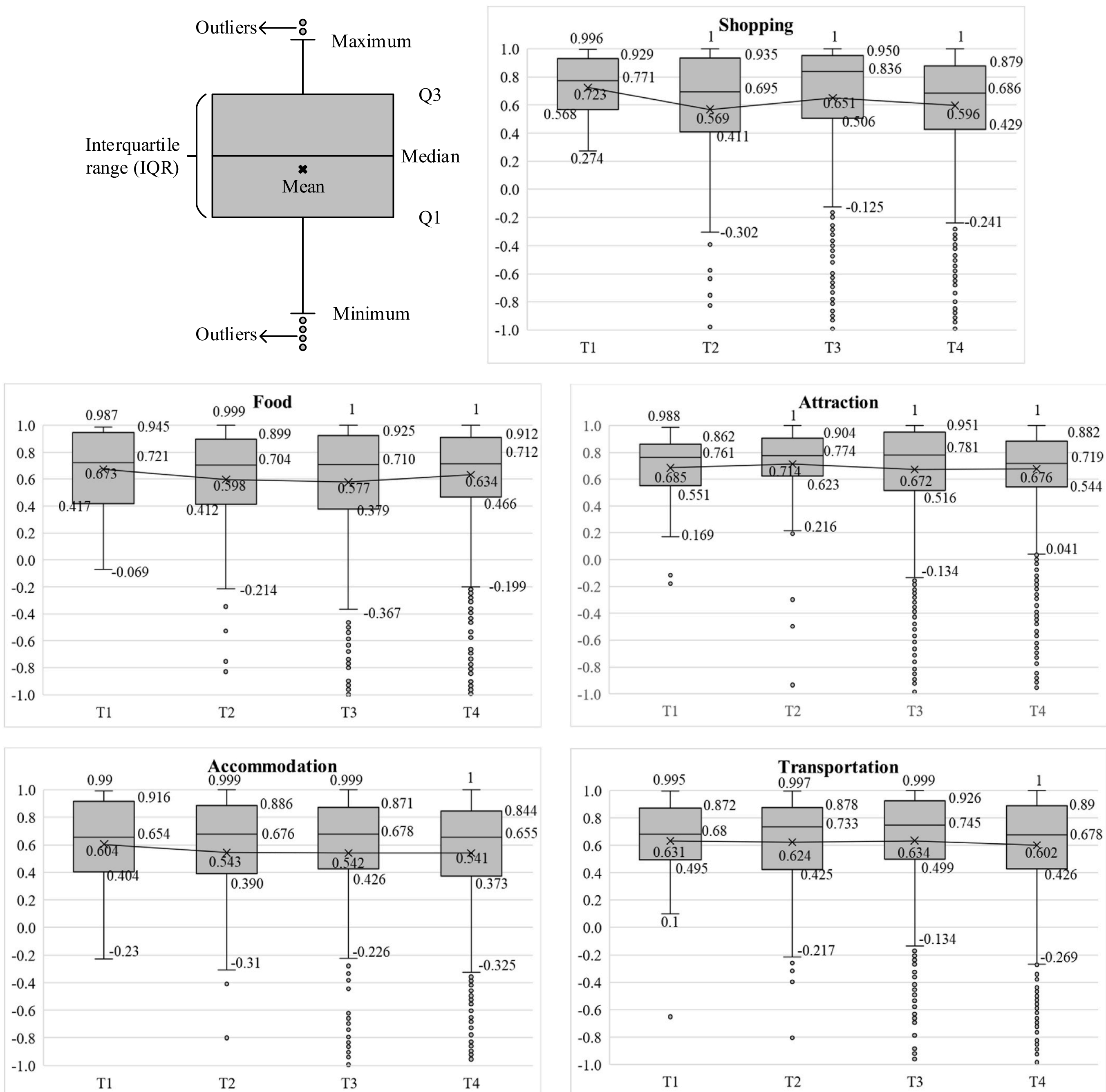

Fig. 5. a. Explanation of Box-whisker plot
Fig. 5b. Shopping performance
Fig. 5c. Food performance
Fig. 5d. Attraction performance
Fig. 5e. Accommodation destination performance
Fig. 5f. Attribute-level destination performance
Fig. 5g. Culture & Art performance
Fig. 5h. Cross-border issue performance.

competitiveness, recognizing that tourist preferences and needs evolve over time. This acknowledgement is crucial as it supports the development of strategies that are responsive to changes in tourist behaviours and market conditions. Previous studies have often overlooked this dynamic aspect (e.g., Lee and Park (2023) and Murayama et al. (2022)), typically treating destination competitiveness as a static concept. This study recognises that tourist preferences and needs evolve over time, which should be considered when assessing destination competitiveness. Meanwhile, results also show that the consistent relevance of the seven identified factors across four different periods, despite shifts in their specific positions, underscores the enduring importance of certain core attributes, such as Attraction and Culture & Art, are Hong Kong's core competitive attributes because they retain their advantageous positions across periods, whereas Accommodation and Cross-border issues

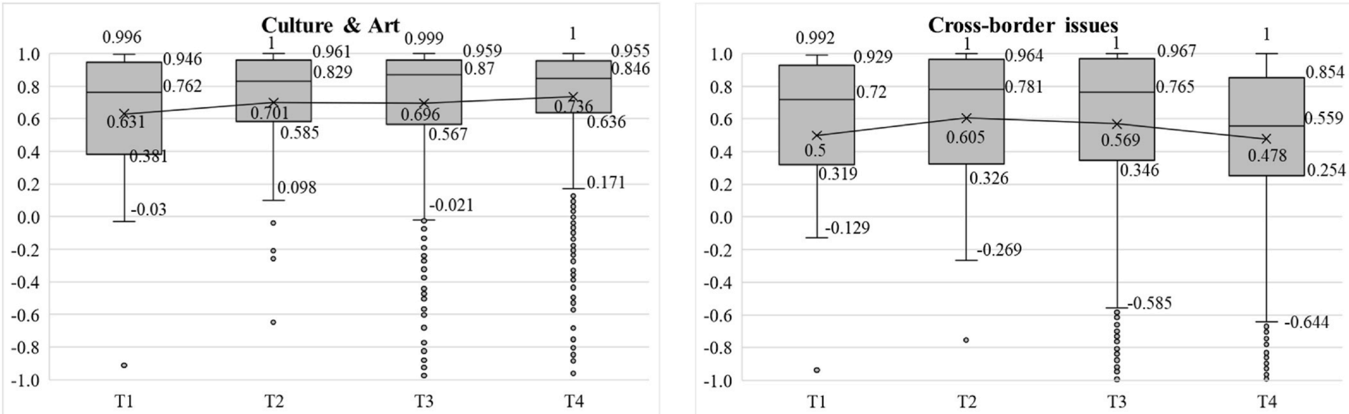

Fig. 5. (*continued*).

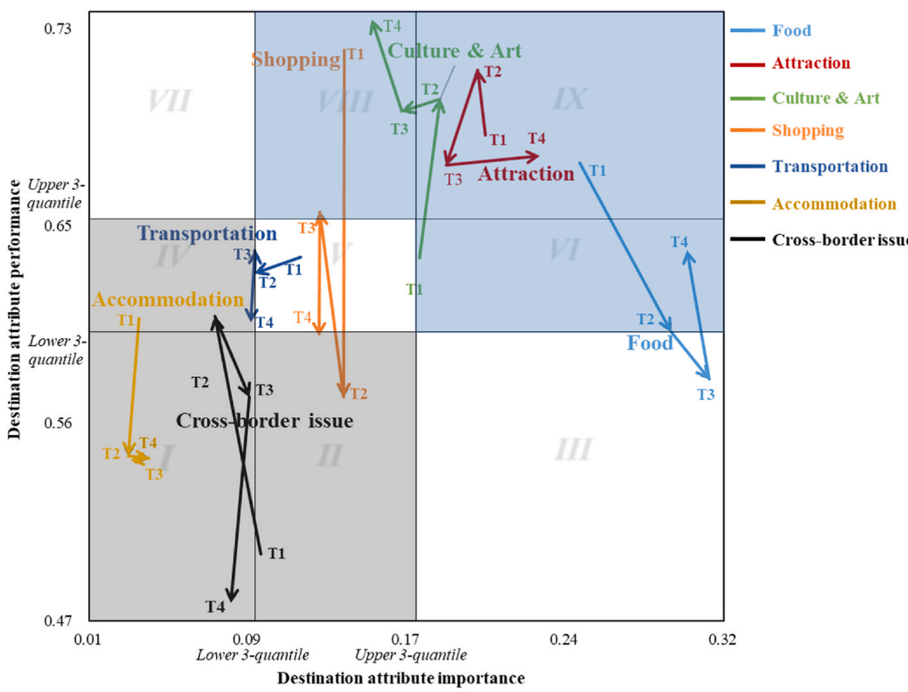

Fig. 6. Destination competitiveness model by McKinsey Matrix.

are edge competitive attributes. In this regard, deeper insights can be attained by holistically evaluating these attributes of destination competitiveness. This finding is crucial as it suggests that while some tourist preferences may fluctuate due to various influences (e.g., economic shifts, cultural trends, technological advancements), certain elements remain consistently significant in shaping tourist experiences and perceptions of a destination's value.

Furthermore, this research contributes to the theoretical framework by employing the McKinsey Matrix to assess destination competitiveness. This innovative application allows for a systematic classification of destination attributes into core and edge competitive factors, which helps in understanding which elements are stable strengths and which are susceptible to fluctuations in competitiveness. This methodological advancement provides a more structured approach to analysing the competitive positioning of destinations over time.

5.2. *Practical implications*

Assessing destination competitiveness is critical for destination authorities to understand their level of competitiveness, which serves as a basis for developing effective countermeasures to enhance their competitiveness. Therefore, we proposed a McKinsey Matrix-based framework to understand the destination competitiveness of Hong Kong through an analysis of tourists' experiences derived from social media posts. Several practical implications for Hong Kong and other destinations can be derived from our findings.

First, our findings will help the Hong Kong authorities understand the attributes of the city that are most important to mainland Chinese tourists: Food, Shopping, Attraction, Accommodation, Transportation, Culture & Art, and Cross-border issues. Quantifying the importance of these attributes will facilitate the authorities' decision-making about which attributes should be prioritised for development. For instance, Food, Culture & Art, and Attraction are the three most important attributes for mainland Chinese tourists, and thus the Hong Kong authorities should ensure they continue to perform well.

Second, we identified Attraction and Culture & Art as the core

Table 5
Opinions expressing dissatisfaction (T3 & T4).

Attribute	Negative opinions
Food	Not allowed to bring own food and drinks, no hot water, old restaurant, poor taste, low-end night market, not cheap, expensive snacks and food, few Jenny Bear cookie flavours
Shopping	Cash only, poor attitude of the staff, expensive pharmacy, very small stores, non-refundable handling fee for convenience store purchases, can only carry two cans of milk powder, no online payment supported.
Attraction	Landmarks are incomplete, a few sidewalks in Kennedy Town are unsafe, too many tourists in Tsim Sha Tsui and Mongkok, Temple Street is not lively, and expensive admission fee.
Cross-border issues	High currency exchange fee, old ports, need to fill in declaration documents for border crossing, inability to buy data for mobile sim cards, slow border crossing process, poor exchange rate
Accommodation	Expensive, cash only, no plugs, no Internet, poor facilities, no toiletries, poor service attitude, no luggage storage, no refund, small room size, no adapters available
Transportation	Disorganised MTR station, few ticket machines, long queues, don't know how to check Octopus balance, low frequency of high-speed train, cabs charge for luggage in the trunk, cabs drive around in circles and get stuck in traffic, fines for mistakenly entering first class (MTR)
Culture & Art	Vanishing culture of light boards worse than the Hong Kong I remember, traditional skills are uncommon and cheongsams are becoming out of fashion, the glory of Hong Kong movies is gone.

competitive attributes of Hong Kong in attracting mainland China tourists. The destination should be aware of its core advantage and actively promote and sustain these attributes to attract more tourists. We also observed that Hong Kong's Shopping and Food attributes are declining in competitiveness, suggesting that the authority should take prompt countermeasures to reverse this trend. The identification of factors that cause tourist dissatisfaction in Section 4.5 should facilitate the development of effective strategies to increase satisfaction, such as improving the environment and decor of restaurants, improving the attitude of shop staff, and promoting the use of electronic payments for shopping. Similarly, we identified the edge competitive attributes of Hong Kong, including Accommodation and Cross-border issues. Our results support the widely held opinion that the cost of staying in Hong Kong is very high. Therefore, the Hong Kong authority could consider launching promotional campaigns in conjunction with hotels to minimise tourists' negative experiences, thereby enhancing its competitiveness in this regard. Cross-border issues also hurt mainland Chinese tourists' travel experiences, particularly the high currency exchange fees, the inconvenience of mobile sim cards, and delays in crossing the border. Hence, the authority should address these issues to improve the competitive position of attributes such as Accommodation and Cross-border issues.

The competitiveness framework developed in this work can be applied to other destinations to understand the evolution of their competitiveness and to generate specific measures to enhance their competitiveness. In the study focusing on Hong Kong, the timeline was divided into four distinct periods (T1 to T4) to capture changes in tourist experiences in relation to significant events and trends affecting travel behaviour. For other destinations, the number of periods may vary depending on the research question and the specific context of those destinations. There is no rigid rule for determining the number of periods, and it should be guided by the research objectives and the availability and relevance of data.

5.3. Limitations of the study and future work

One limitation of our study is in terms of sample representativeness, our study utilised data from mainland Chinese tourists visiting Hong Kong, primarily from Xiaohongshu and Dianping. While this provided valuable insights from a significant market segment, the scope could be broadened in future research to include a more diverse range of tourists, encompassing different nationalities, cultural backgrounds, and travel motivations. This would ensure a more comprehensive and representative sample, leading to findings that are generalisable across a broader spectrum of the tourist population. Additionally, such expansion would offer richer insights into the varied expectations and experiences of different tourist demographics, which are critical for a multi-faceted evaluation of destination competitiveness.

Addressing future research directions could also investigate factors influencing destination competitiveness, which can involve a more granular analysis of specific attributes that influence tourists' perceptions and decisions. Factors such as economic conditions, socio-cultural elements, and sustainability practices will be examined in depth to understand their real time impacts on destination attractiveness.

CRediT authorship contribution statement

Jinyan Chen: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Jie Wu:** Writing – original draft, Visualization, Methodology, Data curation. **Dan Wang:** Writing – review & editing, Supervision. **Bela Stantic:** Writing – original draft, Methodology, Data curation.

Declaration of competing interest

None.

Acknowledgements

This research was supported by the Hong Kong Polytechnic University Research Grant Council (Project ID: P0040524). We appreciate the support and funding that Hong Kong Polytechnic University has provided, which allows us to conduct the work.

References

Abreu Novais, M., Ruhanen, L., & Arcodia, C. (2018). Destination competitiveness: A phenomenographic study. *Tourism Management, 64*, 324–334. https://doi.org/10.1016/j.tourman.2017.08.014

Alaei, A. R., Becken, S., & Stantic, B. (2019). Sentiment analysis in tourism: Capitalizing on big data. *Journal of Travel Research, 58*(2), 175–191. https://doi.org/10.1177/0047287517747753

Albayrak, T. (2015). Importance performance competitor analysis (IPCA): A study of hospitality companies. *International Journal of Hospitality Management, 48*, 135–142. https://doi.org/10.1016/j.ijhm.2015.04.013

Albayrak, T., & Caber, M. (2015). Prioritisation of the hotel attributes according to their influence on satisfaction: A comparison of two techniques. *Tourism Management, 46*, 43–50. https://doi.org/10.1016/j.tourman.2014.06.009

Albayrak, T., Cengizci, A. D., Caber, M., & Fong, L. H. N. (2021). Big data use in determining competitive position: The case of theme parks in Hong Kong. *Journal of Destination Marketing & Management, 22*, Article 100668. https://doi.org/10.1016/j.jdmm.2021.100668

Azzopardi, E. (2011). *The international competitiveness of Malta as a tourist destination.* Robert Gordon University.

Baidu. (2018). PaddlePaddle. Retrieved from https://github.com/PaddlePaddle/PaddleHub. (Accessed 20 September 2022).

Bi, J.-W., Liu, Y., Fan, Z.-P., & Zhang, J. (2019). Wisdom of crowds: Conducting importance-performance analysis (IPA) through online reviews. *Tourism Management, 70*, 460–478. https://doi.org/10.1016/j.tourman.2018.09.010

Blazquez-Resino, J. J., Gutierrez-Broncano, S., & Gołąb-Andrzejak, E. (2022). Neuroeconomy and neuromarketing: The study of the consumer behaviour in the COVID-19 context. *Frontiers in Psychology, 13*, Article 822856. https://doi.org/10.3390/su13073791

Cao, L. (2024). From online to onsite: Wanghong economy as the new engine driving China's urban development. *Environment & Planning A, 353*. https://doi.org/10.1177/0308518X231224142

Chen, J., Becken, S., & Stantic, B. (2019). Lexicon based Chinese language sentiment analysis method. *Computer Science and Information Systems, 16*(2), 639–655. https://doi.org/10.2298/CSIS181015013C

Chen, J., Becken, S., & Stantic, B. (2022). Assessing destination satisfaction by social media: An innovative approach using Importance-Performance Analysis. *Annals of*

Tourism Research, 93, Article 103371. https://doi.org/10.1016/j.annals.2022.103371
Cheng, L. C., Chen, K., Lee, M. C., & Li, K. M. (2021). User-Defined SWOT analysis – a change mining perspective on user-generated content. *Information Processing & Management, 58*(5), Article 102613. https://doi.org/10.1016/j.ipm.2021.102613
Chin, W. L., Haddock-Fraser, J., & Hampton, M. P. (2017). Destination competitiveness: Evidence from Bali. *Current Issues in Tourism, 20*(12), 1265–1289. https://doi.org/10.1080/13683500.2015.1111315
Cimbaljević, M., Stankov, U., & Pavluković, V. (2019). Going beyond the traditional destination competitiveness–reflections on a smart destination in the current research. *Current Issues in Tourism, 22*(20), 2472–2477. https://doi.org/10.1080/13683500.2018.1529149
Cracolici, M. F., & Nijkamp, P. (2009). The attractiveness and competitiveness of tourist destinations: A study of southern Italian regions. *Tourism Management, 30*(3), 336–344. https://doi.org/10.1016/j.tourman.2008.07.006
Crouch, G. I. (2011). Destination competitiveness: An analysis of determinant attributes. *Journal of Travel Research, 50*(1), 27–45. https://doi.org/10.1177/0047287510362776
Deng, J., & Li, J. (2019). Determination of derived importance of a tourism destination: A comparison of indirect methods. *Current Issues in Tourism, 22*(4), 456–475. https://doi.org/10.1080/13683500.2018.1444588
Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2018). BERT:Pre-training of deep bidirectional transformers for language understanding. *Google*. Retrieved from https://arxiv.org/pdf/1810.04805v2.pdf.
Dickinger, A., & Költringer, C. (2011). Extracting destination representation and competitiveness from online content. *Information Technology & Tourism, 13*(4), 327–339.
Dwyer, L., & Kim, C. (2003). Destination competitiveness: Determinants and indicators. *Current Issues in Tourism, 6*(5), 369–414. https://doi.org/10.1080/13683500308667962
Dyson, R. G. (2004). Strategic development and SWOT analysis at the university of Warwick. *European Journal of Operational Research, 152*(3), 631–640. https://doi.org/10.1016/s0377-2217(03)00062-6
Fernandes, T., & Fernandes, F. (2018). Sharing dissatisfaction online: Analyzing the nature and predictors of hotel guests negative reviews. *Journal of Hospitality Marketing & Management, 27*(2), 127–150.
Fyall, A., & Garrod, B. (2020). Destination management: A perspective article. *Tourism Review, 75*(1), 165–169. https://doi.org/10.1108/TR-07-2019-0311
Gao, S., Tang, O., Wang, H., & Yin, P. (2018). Identifying competitors through comparative relation mining of online reviews in the restaurant industry. *International Journal of Hospitality Management, 71*, 19–32. https://doi.org/10.1016/j.ijhm.2017.09.004
Ghiassi, M., & Lee, S. (2018). A domain transferable lexicon set for Twitter sentiment analysis using a supervised machine learning approach. *Expert Systems with Applications, 106*, 197–216. https://doi.org/10.1016/j.eswa.2018.04.006
Gómez-Vega, M., & J Picazo-Tadeo, A. (2019). Ranking world tourist destinations with a composite indicator of competitiveness: To weigh or not to weigh? *Tourism Management, 72*, 281–291. https://doi.org/10.1016/j.tourman.2018.11.006
Guido, G. (1998). The dichotic theory of salience: A framework for assessing attention and memory. *ACR European Advances*.
Gupta, S., Malhotra, N. K., Czinkota, M., & Foroudi, P. (2016). Marketing innovation: A consequence of competitiveness. *Journal of Business Research, 69*(12), 5671–5681.
Hall, J., O'Mahony, B., & Gayler, J. (2017). Modelling the relationship between attribute satisfaction, overall satisfaction, and behavioural intentions in Australian ski resorts. *Journal of Travel & Tourism Marketing, 34*(6), 764–778. https://doi.org/10.1080/10548408.2016.1232672
Hu, N., Zhang, T., Gao, B., & Bose, I. (2019). What do hotel customers complain about? Text analysis using structural topic model. *Tourism Management, 72*, 417–426.
Huang, G. I., Liu, J. A., & Wong, I. A. (2021). Micro-celebrity restaurant manifesto: The roles of innovation competency, foodstagramming, identity-signaling, and food personality traits. *International Journal of Hospitality Management, 97*(April), Article 103014. https://doi.org/10.1016/j.ijhm.2021.103014
Jiang, Q., Chan, C. S., Eichelberger, S., Ma, H., & Pikkemaat, B. (2021). Sentiment analysis of online destination image of Hong Kong held by mainland Chinese tourists. *Current Issues in Tourism, 24*(17), 2501–2522. https://doi.org/10.1080/13683500.2021.1874312
Kubickova, M., & Martin, D. (2020). Exploring the relationship between government and destination competitiveness: The TALC model perspective. *Tourism Management, 78*. https://doi.org/10.1016/j.tourman.2019.104040
Lai, P.-H., Gudergan, S., Young, T., & Lee, K. (2021). Resident intention to invite friends, relatives, and acquaintances: The dynamic process of place identity as a motivator. *Tourism Management, 84*. https://doi.org/10.1016/j.tourman.2020.104251
Lee, J. S., & Park, S. (2023). A cross-cultural anatomy of destination image: An application of mixed-methods of UGC and survey. *Tourism Management, 98* (February), Article 104746. https://doi.org/10.1016/j.tourman.2023.104746
Leung, D., Law, R., Hoof, H. Van, & Buhalis, D. (2013). Social media in tourism and hospitality: A literature review. *Journal of Travel & Tourism Marketing, 30*(1–2), 3–22.
Levy, S. E., Duan, W., & Boo, S. (2013). An analysis of one-star online reviews and responses in the Washington, D.C., Lodging Market. *Cornell Hospitality Quarterly, 54*(1), 49–63.
Li, Y., Huang, H., Chen, Q., Fan, Q., & Quan, H. (2021). Research on a product quality monitoring method based on multi scale PP-YOLO. *IEEE Access, 9*, 80373–80387. https://doi.org/10.1109/ACCESS.2021.3085338
Li, H., Ji, H., Liu, H., Cai, D., & Gao, H. (2022). Is a picture worth a thousand words? Understanding the role of review photo sentiment and text-photo sentiment disparity using deep learning algorithms. *Tourism Management, 92*(March), Article 104559. https://doi.org/10.1016/j.tourman.2022.104559
Li, S. N., Li, H., Song, H., & Chen, M. (2022). Mitigating tourism social costs during a pandemic: Evaluating residents' perceptions and behavioral intentions. *Journal of Travel Research, 61*(3), 493–510. https://doi.org/10.1177/00472875211000447
Li, Y., Yan, X., Wang, Z., Ma, M., Zhang, B., & Jia, Z. (2023). Comparison of the users' attitudes toward cannabidiol on social media platforms: Topic Modeling study. *JMIR Public Health and Surveillance, 9*, Article e34132.
Liu, Z., Qin, C. X., & Zhang, Y. J. (2021). Mining product competitiveness by fusing multisource online information. *Decision Support Systems, 143*, Article 113477. https://doi.org/10.1016/j.dss.2020.113477
Liu, Z., Wang, A., Weber, K., Chan, E. H. W., & Shi, W. (2022b). Categorisation of cultural tourism attractions by tourist preference using location-based social network data: The case of Central, Hong Kong. *Tourism Management, 90*, Article 104488.
Liu, J., Yu, Y., Mehraliyev, F., Hu, S., & Chen, J. (2022). What affects the online ratings of restaurant consumers: A research perspective on text-mining big data analysis. *International Journal of Contemporary Hospitality Management, 34*(10), 3607–3633. https://doi.org/10.1108/IJCHM-06-2021-0749
Lopes, A. P. F., Muñoz, M. M., & Alarcón-Urbistondo, P. (2018). Regional tourism competitiveness using the PROMETHEE approach. *Annals of Tourism Research, 73*, 1–13. https://doi.org/10.1016/j.annals.2018.07.003
Manosuthi, N., Lee, J. S., & Han, H. (2020). Impact of distance on the arrivals, behaviours and attitudes of international tourists in Hong Kong: A longitudinal approach. *Tourism Management, 78*(June 2019), Article 103963. https://doi.org/10.1016/j.tourman.2019.103963
Mior Shariffuddin, N. S., Azinuddin, M., Hanafiah, M. H., & Wan Mohd Zain, W. M. A. (2022). A comprehensive review on tourism destination competitiveness (TDC) literature. *Competitiveness Review: An International Business Journal*. https://doi.org/10.1108/cr-04-2021-0054
Murayama, T., Brown, G., Hallak, R., & Matsuoka, K. (2022). Tourism destination competitiveness: Analysis and strategy of the Miyagi Zaō mountains area, Japan. *Sustainability, 14*(15). https://doi.org/10.3390/su14159124
Neto, A. Q., Dimmock, K., Lohmann, G., & Scott, N. (2020). Destination competitiveness: How does travel experience influence choice? *Current Issues in Tourism, 23*(13), 1673–1687. https://doi.org/10.1080/13683500.2019.1641070
Parra-López, E., & Oreja-Rodríguez, J. R. (2014). Evaluation of the competiveness of tourist zones of an island destination: An application of a Many-Facet Rasch Model (MFRM). *Journal of Destination Marketing & Management, 3*(2), 114–121. https://doi.org/10.1016/j.jdmm.2013.12.007
Pesce, M., Shi, C., Critto, A., Wang, X., & Marcomini, A. (2018). SWOT analysis of the application of international standard ISO 14001 in the Chinese context. A case study of Guangdong Province. *Sustainability, 10*(9), 1–19. https://doi.org/10.3390/su10093196
Porter, M. E. (1980). Competitive strategy: Techniques for analyzing industries and competitors. *Editorial Free Pr.* ISBN, 13, 9780029253601.
Qu, Y., Rong, W., Chen, H., Ouyang, Y., & Xiong, Z. (2018). Influencing factors analysis for a social network web based payment service in China. *Journal of Theoretical and Applied Electronic Commerce Research, 13*(3), 99–113. https://doi.org/10.4067/S0718-18762018000300106
Rašovská, I., Kubickova, M., & Ryglová, K. (2021). Importance–performance analysis approach to destination management. *Tourism Economics, 27*(4), 777–794. https://doi.org/10.1177/1354816620903913
Richards, G., King, B., & Yeung, E. (2020). Experiencing culture in attractions, events and tour settings. *Tourism Management, 79*(February), Article 104104. https://doi.org/10.1016/j.tourman.2020.104104
Ritchie, J. R. B., & Crouch, G. I. (2003). *The competitive destination: A sustainable tourism perspective*. Cabi.
Serrano-Guerrero, J., Olivas, J. A., Romero, F. P., & Herrera-Viedma, E. (2015). Sentiment analysis: A review and comparative analysis of web services. *Information Sciences, 311*, 18–38. https://doi.org/10.1016/j.ins.2015.03.040
Shakibaei, S., de Jong, G. C., Alpkökin, P., & Rashidi, T. H. (2021). Impact of the COVID-19 pandemic on travel behavior in istanbul: A panel data analysis. *Sustainable Cities and Society, 65*(September). https://doi.org/10.1016/j.scs.2020.102619
Shan, W., Wang, J., Shi, X., & David Evans, R. (2024). The impact of electronic word-of-mouth on patients' choices in online health communities: A cross-media perspective. *Journal of Business Research, 173*(December 2022), Article 114404. https://doi.org/10.1016/j.jbusres.2023.114404
Shen, L., Shuai, C., Jiao, L., Tan, Y., & Song, X. (2017). Dynamic sustainability performance during urbanization process between BRICS countries. *Habitat International, 60*, 19–33. https://doi.org/10.1016/j.habitatint.2016.12.004
Soares, J. C., Domareski Ruiz, T. C., & Ivars Baidal, J. A. (2021). Smart destinations: A new planning and management approach? *Current Issues in Tourism, 0*(0), 1–16. https://doi.org/10.1080/13683500.2021.1991897
Sparks, B. A., & Browning, V. (2010). Complaining in cyberspace: The motives and forms of hotel guests' complaints online. *Journal of Hospitality Marketing & Management, 19*(7), 797–818. https://doi.org/10.1080/19368623.2010.508010
Sun, J. (2012). Jieba Chinese word segmentation tool. Retrieved from https://github.com/fxsjy/jieba. (Accessed 20 August 2022).
Tegegne, W. A., Moyle, B. D., & Becken, S. (2018). A qualitative system dynamics approach to understanding destination image. *Journal of Destination Marketing & Management, 8*, 14–22. https://doi.org/10.1016/j.jdmm.2016.09.001
Tsang, D., Heung, S., & Yeo, R. (2023). Hong Kong aims for January 8 reopening of border with mainland China, city's No 2 official says in clearest indication yet on long-awaited date. *South China Morning Post*. Retrieved from https://www.scmp.com/news/hong-kong/hong-kong-economy/article/3205222/hong-kong-eyeing-jan

uary-8-reopening-border-mainland-china-citys-no-2-official-says-clearest. (Accessed 30 October 2023).
Wu, J., Zhang, J., & Zhao, N. (2023). How to boost e-commerce for poverty alleviation? A perspective on competitiveness analysis using online reviews. *Electronic Commerce Research*. https://doi.org/10.1007/s10660-023-09708-2
Yang, T., Wu, J., & Zhang, J. (2024). Knowing how satisfied/dissatisfied is far from enough: A comprehensive customer satisfaction analysis framework based on hybrid text mining techniques. *International Journal of Contemporary Hospitality Management, 36*(3), 873–892. https://doi.org/10.1108/IJCHM-10-2022-1319
Yonezawa, K., & Richards, T. J. (2016). Competitive package size decisions. *Journal of Retailing, 92*(4), 445–469.
Yuan, Y., You, T., Xu, T., & Yu, X. (2022). Customer-oriented strategic planning for hotel competitiveness improvement based on online reviews. *Sustainability, 14*(22), 1–30. https://doi.org/10.3390/su142215299
Zhang, N., Zhang, R., Pang, Z., Liu, X., & Zhao, W. (2021). Mining express service innovation opportunity from online reviews. *Journal of Organizational and End User Computing, 33*(6), 1–15. https://doi.org/10.4018/joeuc.20211101.oa3
Zheng, D., Luo, Q., & Ritchie, B. W. (2021). Afraid to travel after COVID-19? Self-Protection, coping and resilience against pandemic 'travel fear.'. *Tourism Management, 83*, Article 104261.
Zhou, X., & Chen, Z. (2023). Destination attraction clustering: Segmenting tourist movement patterns with geotagged information. *Tourism Geographies, 25*(2–3), 797–819. https://doi.org/10.1080/14616688.2021.2006769

Dr. Jinyan Chen is a Research Assistant Professor in the School of Hotel and Tourism Management at the Hong Kong Polytechnic University. She is also an adjunct fellow with the Griffith Institute for Tourism, Australia. Her main research interests include understanding tourist behaviour, modelling tourist travel patterns, sentiment analysis, network analysis, and relying on social media and big data analytics.

Dr Jie WU is working as a research assistant in the School of Hotel and Tourism Management, the Hong Kong Polytechnic University. His research interests include understanding tourist satisfaction and big data analysis.

Dr. Dan Wang is currently an Associate Professor in the School of Hotel & Tourism Management, The Hong Kong Polytechnic University. Her research focuses on the impact of mobile Internet on tourists.

Professor Bela Stantic is Professor in Computer Science and founder and Director of "Big Data and Smart Analytics" Lab at Griffith University. Professor Stantic is internationally recognized in field of data analytics and efficient management of complex data structures, such as found in Big Data. He was invited to give many Keynotes and invited talks at highly ranked International conferences and prestigious institutions as well as he has been doing the journal editorial duties and reviews of many top ranked journals.